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Battery electric vehicles in Japan: Human mobile behavior based adoption potential analysis and policy target response

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HIGHLIGHTS

- BEV adoption analysis with 1.6 millon people for 3 years travel behavior data is developed.
- Human travel mode detection model and travel habit clustering model are proposed.
- Diverse consumption attitudes are taken into consideration.
- A novel weighted vehicle adoption potential metric is introduced.
- The detailed advises for policy target response are presented.

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ABSTRACT

With the pressing demand of climate change mitigation, the rapid technological development and market adoption of battery electric vehicles are imperative. However, the diverse consumption attitudes and their interactions, which are rarely considered, can significantly affect the adoption potential of battery electric vehicles. On the basis of three years of global positioning system data of 1.6 million people, we estimated the travel and adoption demands of battery electric vehicles in Japan considering diverse consumption attitudes. Under the current construction conditions for public charging systems and charging technologies, the adoption potential of battery electric vehicles may not be as promising as previously expected, and the government still faces great pressure to respond to the market share target. Given the current level of battery technology, technical and policy improvements such as fast charging, reducing the production cost, perfecting the public charging infrastructure, and increasing purchasing subsidies were found to be more effective than improving the battery capacity at increasing the adoption potential of battery electric vehicles.

1. Introduction

The current global energy market is in a transition period. Driven by technological advances and environmental needs, energy consumption is taking a turn towards clean and low-carbon energy [1]. Many countries are preparing to set a time at which internal combustion engine vehicles (ICEVs) will exit the market. As the world's third-largest economy, Japan has a high demand for energy. The annual demand for primary energy is 445.3 million tons of oil equivalent, and transportation accounts for 24.1% of the total energy consumption [2]. After the Fukushima Daiichi nuclear disaster, Japan increased its imports of natural gas and crude oil in the short term to make up for the power shortage. However, this resulted in more carbon emissions and increased the price of fossil fuels [3]. At present, Japan is restarting some of its nuclear power plants and readjusting its energy structure to reduce carbon emissions and balance its energy self-sufficiency [4]. These factors offer new opportunities for the development of the market for battery electric vehicles (BEVs) [5]. Meanwhile, the Japanese government is also vigorously promoting the development of new energy vehicles [6]. The promotion of BEVs would satisfy the requirements for reducing carbon emissions and relieve Japan's dependence on fossil fuels [7].

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Nomenclature

BEV	battery electric vehicle
CI	charging interval
DAP	daily vehicle adoption potential
DCA	diverse consumption attitude
ELVT	extremely low-frequency vehicle traveler
GPS	global positioning system
HHVT	holiday high-frequency vehicle traveler
ICEV	internal combustion engine vehicle
LVT	low-frequency vehicle traveler
HVT	high-frequency vehicle traveler
OHVT	overall high-frequency vehicle traveler
SR	satisfaction rate of the daily driving travel demand
VCR	velocity change rate
WAP	weighting vehicle adoption potential

However, at present, most BEVs have been designed with a focus on specific uses such as short-distance low-speed use, urban public transport, and tourism purposes [8]. The widespread use of BEVs is still hindered by insufficient technological advancements [9], infrastructure facilities [10], and policy support, and they do not meet the expectations of consumers [11]. The key technologies restricting the marketization of BEVs are those for efficient battery energy storage [12] and quick charging at a low temperature [13]. In addition, the high prices of electric motors, batteries, and motor control systems increase the production cost of BEVs compared to ICEVs, which limits the market potential of BEVs to a certain extent [14]. To promote the electrification of BEVs, the charging and maintenance infrastructure systems need to be improved [15]. The sophistication of these support service systems will directly affect the demand for BEVs [16]. Meanwhile, the BEV market is still immature, and the government has been investigating policies related to the usage, market, and subsidy of BEVs [17]. Further, the promotion of BEVs will impact the development and operational efficiency of urban areas [18]. Thus, the development of BEVs is a challenging sociotechnical issue [19].

Conducting an adoption-potential analysis based on BEV technical indexes is key to connecting the social and technical aspects of this issue. This analysis contributes to the determination of the sensibilities of the technical and economic indicators of BEVs, which can guide BEV companies and the government for the planning of the construction of infrastructure facilities and the creation of policies based on the current demand and technical level.

Many scholars have conducted studies on this issue and provided new research perspectives and experimental methods for analyzing the market potential and policy-making of BEVs [20]. For example, on the basis of GPS data from 744,788 driver trips, Needell et al. [21] analyzed the impact factors for automotive energy consumption by considering the second-by-second velocity and ambient temperature. From the perspectives of the daily vehicle adoption potential (DAP) and gasoline substitution potential, they analyzed the potential for the widespread electrification of personal vehicle travel in the United States. They concluded that affordable BEVs can replace 87% of vehicles driven on a given day without recharging. Li et al. [20] introduced choice experiment to analyze the impact of personal carbon trading on BEVs adopting decision and compared this incentive with other policies. The results showed that except for government subsidy, the personal carbon trading was more powerful than other policies. Zhao et al. [22] proposed a life-cycle cost and emissions model for BEVs in China. The results showed that until 2031, BEVs are not economically competitive compared with ICEVs in the Chinese market. Palencia et al. [23] took japan as an example, proposed a 'two-step' approach to estimate the optimum market penetration of lightweight and electric-drive vehicles in the long-term and the impact on the light-duty vehicle fleet. They found ICEVs and hybrid electric vehicles dominate in the Base scenario, fuel cell hybrid electric vehicles dominate when low cost is prioritized and BEVs occurs when low CO2 emissions are prioritized. Neaimeh et al. [24] analyzed 90,000 fast charge events in the UK and the US and 12,700 driving days collected from 35 BEVs in the UK. The found that fast chargers could help overcome perceived and actual range barriers, and greatly increase the adoption rate of BEVs. Current studies have mainly just chosen one aspect of consumption attitudes to make the comparison between BEVs and ICEVs. Nevertheless, the interactions between those aspects are usually ignored. Due to technical, travel cost, and policy differences (such as restricting the travel time and area of ICEVs, increasing the taxes of ICEVs and fuel, financial subsidies for BEV purchases, and government guidance), BEVs and ICEVs have multiple differences regarding the economy, convenience, traveling comfort, environmental protection, and personal subjective evaluation [25]. Strong interplay will exist between the promotion process for BEVs and the diverse consumption attitudes (DCAs) [26], making adoption analyses and policy planning for BEVs more complex. Therefore, some new questions are worth discussing further. Which factors mainly affect the adoption potential of BEVs? What are the sensitivities and interaction of such factors to the adoption potential of BEVs? And based on those, what effective policies should be put forward by the government to respond to the proposed target?

Here, on the basis of smartphone GPS data from approximately 1.6 million people in Japan over a three-year period, we analyzed the characteristics of human mobile and travel mode preferences during different periods (working days and holidays). We quantitatively derived a statistical classification for vehicle travel behavior. For each classified group, we performed an analysis of the adoption potential of BEVs with multiple dimensions. Finally, policy measures are suggested for the Japanese government to respond to the proposed target.

The contributions of this work are shown as following:

(1) On the basis of three years of GPS data of 1.6 million people, we estimated the travel and adoption demands of BEVs in Japan;
(2) Diverse consumption attitudes of BEVs are taken into the consideration which are also proved to have great impact on the conclusion;
(3) Human travel mode detection model and travel habit clustering model are design to reveal the multiple energy consumption behaviors in human travel;
(4) A new metric, weighted vehicle adoption potential, is proposed to indicate the expectation of satisfying the driving travel demand;
(5) The results show that the adoption potential of BEVs may not be as promising as previously expected, and the government still faces great pressure to respond to the market share target for BEVs.

The remainder of this paper is organized as follows. In Section 2, the data sources of our study are introduced. The two main data-mining methods for travel behaviors—human travel mode detection and travel habit clustering—are proposed in Sections 3 and 4. Section 5 describes the metric definitions used in the future discussion. Section 6 presents the final results solved by proposed methods and metrics. The conclusion is provided in Section 7.

2. Data sources

To address the problem of real-world human mobility, in Japan, NTT DOCOMO INC collected data for an anonymous GPS log dataset, called "Konzatsu-Tokei (R)", from about 1.6 million mobile-phone users, totaling 30 billion GPS records, over a three-year period from August 1, 2010 to July 31, 2013. "Konzatsu-Tokei (R)" Data refers to people flows data collected by individual location data sent from

mobile phone with enabled AUTO-GPS function under users' consent, through the "docomo map navi" service provided by NTT DOCOMO, INC. Those data is processed collectively and statistically in order to conceal the private information. Original location data is GPS data (latitude, longitude) sent in about every a minimum period of 5 min and does not include the information to specify individual such as gender or age.

The battery electric vehicle (BEV) technical data used in our analysis were collected by the MarkLines automotive industry portal [27], which provides production, market, and technical information, along with news, related to the global automotive industry. In addition, ICEV and BEV technical data for the simulation models were based on a previous study [21].

Furthermore, the ambient temperature data used in our simulation models were obtained from the official Japanese weather statistics website [28]. The macro information on the Japanese energy industry is based on reports from the Institute of Energy Economics, Japan [2] and the British Petroleum Statistical Review of World Energy [29], while the policy information was obtained from the Japanese Ministry of Economy, Trade, and Industry [30].

3. Human travel mode detection model

In this research, we build Human Travel Mode Detection Model to identify the travel mode of raw GPS data. For the whole GPS data of one user, this model firstly separates the raw GPS data into stay segments and move segments by the distance and duration of neighboring points. Then the move segments are divided into trajectories based on speed, velocity change rate and the points in rail lines. Finally, we utilize the machine learning method i.e. random forest to classify the trajectories into several travel modes including walk, bike, car and rain.

3.1. Stay and move segments separation

The stay segment of one user's GPS data is a group of consecutive points that represent the user stopping at a location. In this research, the stay segments are identified by the distance and time span of neighboring points which are less than the threshold. In addition to the normal stay points, in the raw GPS data set there are a lot of noise points which has a large distance from its neighboring points. The noise points are removed by the following procedures: firstly we represent the GPS points by Gaussian distribution with the following mean and standard deviation equations:

$$\sigma = \sqrt{\frac{1}{K}\sum_{1}^{K}(p_i-\mu)^2}\ ,where\ \mu = \frac{1}{K}\sum_{1}^{K}(p_i), \tag{1}$$

where p_i is the ith GPS point and K is the total number. Then if the distances from an inner point to its neighbors are larger than $2.6\sigma + \mu$, it will be defined as an outlier and removed from the data set.

3.2. Splitting moving segments

The moving segments are split by the following indicators and procedures. Firstly, the segments are split into walk and non-walk trajectories by the speed threshold 100 m/min. Then velocity change rate defined as the average speed of the current segment compared with the current observed speed is utilized for extracting the change points in non-walk trajectories. The points in rail lines are further extracted to represent the trajectories of railway passengers.

3.3. Traffic mode classification

The traffic mode of each split GPS trajectory are detected by the random forest method. The input features of each trajectory include total distance, time duration, percentage of points in transportation network and speed features including minimum speed, maximum speed, average speed, maximum acceleration, velocity change rate. The output labels of the model are four transportation modes including walk, bike, car and train. We validate our model by test data sets of different transportations modes to check the performance of our model over these modes.

4. Travel habit clustering model

4.1. Human travel habit matrix

Using the human travel mode model, the travel state of each person during each period can be determined. Thus, the ratios of each travel mode for different periods (overall period, work day, holiday) were calculated using the following functions:

$$a_{\mathrm{O}_{m,k}} = \sum_t \sum_p (B_{m,t,p,k}L_{m,t,p}) \Big/ \sum_t \sum_p L_{m,t,p}, \tag{2}$$

$$a_{\mathrm{W}_{m,k}} = \sum_t \sum_p (T_{\mathrm{W}_t}B_{m,t,p,k}L_{m,t,p}) \Big/ \sum_t \sum_p (T_{\mathrm{W}_t}L_{m,t,p}), \tag{3}$$

$$a_{\mathrm{H}_{m,k}} = \sum_t \sum_p (T_{\mathrm{H}_t}B_{m,t,p,k}L_{m,t,p}) \Big/ \sum_t \sum_p (T_{\mathrm{H}_t}L_{m,t,p}), \tag{4}$$

where $a_{\mathrm{O}_{m,k}}$, $a_{\mathrm{W}_{m,k}}$, and $a_{\mathrm{H}_{m,k}}$ are mobile phone user m's ratios of travel mode k during the overall, work-day, and holiday periods, respectively; $L_{m,t,p}$ is the travel distance of mobile phone user m for trajectory p on day t; $B_{m,t,p,k}$ is a binary parameter, when the trajectory travel mode is k (this parameter is equal to 1 or 0); and T_{W_t} and T_{H_t} are binary parameters for the day t when it is a work day or holiday, respectively (the corresponding parameters are equal to 1 or 0).

We consider $a_m = [a_{\mathrm{O}_m}, a_{\mathrm{W}_m}, a_{\mathrm{H}_m}]$ as the travel habit eigenvector of user m. The travel habit matrix for all users $A(N,M)$ can be established from the relation $A = [a_1^{\mathrm{T}}, a_2^{\mathrm{T}}, \cdots, a_M^{\mathrm{T}}]$, where M is the total number of users. Further, N is equivalent to three multiples of K and K is the total number of travel modes.

4.2. Non-negative matrix factorization

The travel habit matrix is high-dimensional and contains considerable sophisticated information; therefore, we assumed that the travel habit information could be characterized in a low-dimensional form. For example, the ratio of vehicle travel for non-vehicle owners may correspond to a considerable proportion of the total population; however, in general, this ratio is considerably low, which could be a salient feature for clustering of this category of individuals regardless of the other travel mode ratios. Therefore, if the travel habits could be mapped into a low-dimensional matrix $U(N,R)$, a corresponding tendency matrix $V(M,R)$ for users could be determined. Here, U is the travel habit feature matrix, V is the user tendency feature matrix, and R represents the number of travel habit features. Hence, the human travel habit matrix can be approximately represented by the product of U and V, i.e., $A \approx UV^{\mathrm{T}}$, $R < M,N$. In this manner, the degree of freedom of the travel habit is decreased from $O(MN)$ to $O((M + N)\cdot R)$.

According to the definitions of U and V, all values of those matrixes must be positive. The alternative least squares method was used to decompose the human travel habit matrix. First, the loss function was generated to represent the decomposition error:

$$C = \sum_n \sum_m [(a_{n,m}-u_n^{\mathrm{T}}v_m)^2 + \lambda(\|u_n\|^2 + \|v_m\|^2)], \tag{5}$$

where λ is the regular coefficient.

Then, the objective was to determine U and V so as to minimize C. Further, random generation of $U^{(0)}$ was necessary, and $U^{(0)}$ was used to solve the corresponding $V^{(0)}$. Then, based on $V^{(0)}$, a new $U^{(1)}$ was

calculated. This process was repeated until the value of C converged to the minimum.

The detailed algorithm is as follows:

1. Randomly generate positive $U^{(0)}$.
2. Incorporate $U^{(0)}$ into the loss function, such that

$$C = \sum_n \sum_m [(a_{n,m} - (u_n^{(0)})^{\mathrm{T}} v_m)^2 + \lambda(\|u_n^{(0)}\|^2 + \|v_m\|^2)], \tag{6}$$

followed by derivation of v_m, where

$$\begin{aligned}\frac{\partial C}{\partial v_m} &= \frac{\partial}{\partial v_m}\left[\sum_n [(a_{n,m} - (u_n^{(0)})^{\mathrm{T}} v_m)^2 + \lambda(\|u_n^{(0)}\|^2 + \|v_m\|^2)]\right] \\ &= 2\sum_n [((u_n^{(0)})^{\mathrm{T}} u_n^{(0)} + \lambda) v_m - a_{n,m} u_n^{(0)}]\end{aligned} \tag{7}$$

Let $\frac{\partial C}{\partial v_m} = 0$. Then,

$$\sum_n [((u_n^{(0)})^{\mathrm{T}} u_n^{(0)} + \lambda) v_m] = \sum_n a_{n,m} u_n^{(0)}. \tag{8}$$

That is,

$$(U^{(0)} U^{(0)\mathrm{T}} + \lambda E) v_m^{(0)} = U^{(0)} a_m^{\mathrm{T}}, \tag{9}$$

$$v_m^{(0)} = (U^{(0)} U^{(0)\mathrm{T}} + \lambda E)^{-1} U^{(0)} a_m^{\mathrm{T}}. \tag{10}$$

As v_m cannot be negative, if $v_m \leqslant 0$, let $v_m = 0$. Thus, $V^{(0)}$can be obtained.

3. Incorporating $V^{(0)}$ into the loss function and using the same derivation method as in Step 2, calculate $U^{(1)}$ from

$$u_n^{(1)} = (V^{(0)} V^{(0)\mathrm{T}} + \lambda E)^{-1} V^{(0)} a_n^{\mathrm{T}}. \tag{11}$$

Further, if $u_n \leqslant 0$, let $u_n = 0$.

4. Steps 2 and 3 are repeated until the value of C converges to a minimum.

4.3. Number of travel habit features

According to the algorithm, the value of R, which represents the number of travel habit features, should be determined before the matrix decomposition. If R is set to a small value, the travel habit can be effectively characterized; however, the decomposition loss may increase. If R is set to a large value, more superfluous features may be generated. Therefore, a sensitivity analysis was conducted to optimize R. As there is a regular penalty term in C, we selected another, more straightforward metric, D, to represent the decomposition loss, where

$$D = \|A - U^{\mathrm{T}} V\|_{\mathrm{F}} / \sqrt{MN}. \tag{12}$$

4.4. Population proportion of each travel habit feature

In this study, the population proportion of each travel habit feature is a significant parameter; here, a weighting method was used. As the final feature matrix V was obtained, the user tendency degree $\alpha_{m,r}$ could be calculated from

$$\alpha_{m,r} = v_{m,r} \Big/ \sum_{r'} v_{m,r'} \tag{13}$$

Then, the population proportion of each travel habit feature P_r could be calculated from

$$P_r = \sum_m \alpha_{m,r} / M. \tag{14}$$

5. Metric definitions

5.1. Satisfaction rate of vehicle travel energy demand

The vehicle travel energy demand of the subjects was measured in units of day. The travel energy demand of user m during day t was represented by $E_{m,t}$, which could be determined using the TripEnergy model [21] based on the travel trajectory information and ambient temperature. The satisfaction rates of the daily vehicle travel energy demand R_{D}, holiday daily vehicle travel energy demand R_{DH}, and vehicle travel energy demand under a certain charging interval (CI) R_{I} for smartphone user m were computed as

$$R_{\mathrm{D}_m} = \sum_t \delta(E_{m,t} < E_{charge}) / T, \tag{15}$$

$$R_{\mathrm{DH}m} = \sum_t T_{\mathrm{H}_t} \delta(E_{m,t} < E_{charge}) \Big/ \sum_t T_{\mathrm{H}_t}, \tag{16}$$

$$R_{\mathrm{I}_m} = \sum_t \delta\left(\sum_{t'=t}^{t+\mathrm{CI}} E_{m,t'} < E_{charge}\right) \Big/ (T - \mathrm{CI}), \tag{17}$$

respectively, where δ is a logical function. Thus, if the inequalities in brackets in the above equations are true, the output is 1. Otherwise, the output is 0. E_{charge} is the battery capacity benchmark.

5.2. Daily vehicle adoption potential

In this study, the daily vehicle adoption potential (DAP) was considered as the portion of vehicle-days for which a BEV can replace an ICEV on one charge, expressed as

$$\mathrm{DAP} = \int_0^{E_{charge}} p_{\mathrm{D}}(E) \mathrm{d}E, \tag{18}$$

where $p_{\mathrm{D}}(E)$ is the vehicle-day energy distribution.

However, multiple scenarios were considered for the DAP in this study and, thus, the detailed definition of $p_{\mathrm{D}}(E)$ varied. In Fig. 3, three different DAPs are considered: DAP(E_{O},SR = 90%), DAP(E_{H},SR = 90%), and DAP(E_{O},SR = 100%). These metrics were computed as follows:

$$\mathrm{DAP}(E_{\mathrm{O}}, \mathrm{SR} = 90\%) = \sum_m \delta(R_{\mathrm{D}_m} \geqslant 90.0\%) / M, \tag{19}$$

$$\mathrm{DAP}(E_{\mathrm{H}}, \mathrm{SR} = 90\%) = \sum_m \delta(R_{\mathrm{DH}_m} \geqslant 90.0\%) / M, \tag{20}$$

$$\mathrm{DAP}(E_{\mathrm{O}}, \mathrm{SR} = 100\%) = \sum_m \delta(R_{\mathrm{D}_m} \geqslant 99.5\%) / M. \tag{21}$$

As GPS data may contain error and noise, we consider 99.5% as corresponding to a 100% satisfaction rate; hence, the impact of the error and noise on the result was diminished.

5.3. Weighted vehicle adoption potential

The expectation of satisfying the driving travel demand has a considerable impact on BEV adoption analysis, as shown in the main paper; therefore, a new metric, the weighting vehicle adoption potential (WAP), was proposed, which is defined as follows:

$$\mathrm{WAP} = \int_0^{E_{charge}} p_{\mathrm{W}}(E) \mathrm{d}E, \tag{22}$$

where $p_{\mathrm{W}}(E)$ is the weighted distribution of the vehicle-day energy. This metric is computed as

$$\mathrm{WAP} = \int_0^{100\%} \left[\omega(r) \sum_m \delta(R_{\mathrm{I}_m} \geqslant r)\right] \mathrm{d}r \Big/ M, \tag{23}$$

$$\omega(r) = \begin{cases} 0 & r < 60\% \\ 1.3\% & 60\% \leqslant r < 80\% \\ 6.5\% & 80\% \leqslant r < 90\% \\ 87.9\% & 90\% \leqslant r < 99.5\% \\ 100\% & r \geqslant 99.5\% \end{cases}, \quad (24)$$

where $\omega(r)$ is the weighting function. The parameters of this function could be determined by questionnaire surveys for the purchase intentions (Fig. 1(c)).

6. Result and discussion

6.1. Purchase intentions and factors of concern for BEVs

Surveys of the purchase intentions and factors of concern for BEVs were conducted, and the results are shown in Fig. 1. In the surveys conducted in this study, 2193 valid internet questionnaires were obtained from vehicle owners. In response to the question "*Is your main travel mode by vehicle?*," 1034 and 1159 respondents chose "Yes" and "No," respectively. Fig. 1(a) is the survey results of the purchase attitudes for BEVs. We classified people as high-frequency vehicle travelers (HVTs) and low-frequency vehicle travelers (LVTs). The dark and light colors in the outer circle represent the LVTs and HVTs, respectively. Fig. 1(b) is the survey results of the factors of concern for BEVs. "Others" include concerns about customer service, horsepower difference, driving safety, and so on. c Fig. 1(b) is the survey results of expectation of satisfying the driving travel demand for adopting BEVs. The purchase intentions for BEVs differ between low-frequency vehicle travelers (LVTs) and high-frequency vehicle travelers (HVTs). LVTs are prone to adopting BEVs, whereas HVTs are inclined to have a neutral attitude. Regarding the factors of concern, the proportion of the limitation range remained the highest, and the other concerns of the inconvenience of charging, the high price, and the short battery life accounted for 22%, 23%, and 12%, respectively. It is worth noting that concern of a short battery life may also represent people's concern about the maintenance cost to a certain extent. Thus, apart from the limitation range, purchase and maintenance (P&M) costs and charging convenience are also dominant concerns affecting the adoption potential of BEVs. We also found a difference in the expectation of satisfying the driving travel demand for adopting BEVs. Most respondents felt that satisfying the driving travel demand by 90% is a key technical index for adopting BEVs, and 12.1% respondents required 100% satisfaction. Thus, to analyze the adoption potential of BEVs, at least three more dimensions should be considered in the DCAs: the driving frequency based human-mobile-behavior classification, multiple factors of concern, and the difference in the expectation of satisfaction.

6.2. Recognition and classification model of the human travel mode

We analyzed the daily GPS data from people for three years by the human-travel-mode detection model (Section 2). Taking the moving speed, the moving area, and the degree of matching between the moving route and the public transportation route as the input indexes of the model, the travel mode of each person in each period could be estimated, as shown in Fig. 2. (a) is for vehicle travel track, (b) is for bicycle, (c) is for walk and (d) is for train.

Unsupervised clustering was conducted to classify people by using the indicators of the proportions of each travel mode during different periods (overall period, working days, and holidays). The results show that four main types of human driving behaviors are prominent: overall high-frequency vehicle travelers (OHVTs), holiday high-frequency vehicle travelers (HHVTs), LVTs, and extremely low-frequency vehicle travelers (ELVTs). We assumed that ELVTs have little travel demand for vehicles currently in use; therefore, they were excluded from our analysis of adoption potential of BEVs. The proportions of the four types of travelers are 13.6%, 16.7%, 36.4%, and 33.3%, respectively. According to the previous survey (Fig. 1), approximately 34.5% of people have a positive attitude towards the adoption of BEVs and will be the predominant potential customers for BEVs. However, the urban proportion of OHVTs and HHVTs is much larger than that of LVTs and ELVTs. This result reveals that as the cost and inconvenience of vehicle travel increase in Japanese cities, the urban proportion tends to choose public transport and green travel modes.

6.3. Analysis of the daily adoption potential

The DAP is a typical metric used in analyses of the adoption potential of BEVs based on mobile GPS data. However, a certain daily GPS sample may not be sufficiently comprehensive to represent the real demand. Here, on the basis of three years of mobile GPS data of people in Japan and the trip energy model, we propose three scenarios to conduct a DAP analysis for the OHVTs, HHVTs, and LVTs (Fig. 3): 1. meeting 90% of the daily travel energy demand in all periods, 2. meeting 90% of the holiday daily travel energy demand, and 3. meeting 100% of the daily travel energy demand in all periods. We also selected four major recently launched BEVs in Japan—the Nissan Leaf, Honda Clarity Electric, Mazda Demio EV, and Toyota Scion iQ—and the ARPA-

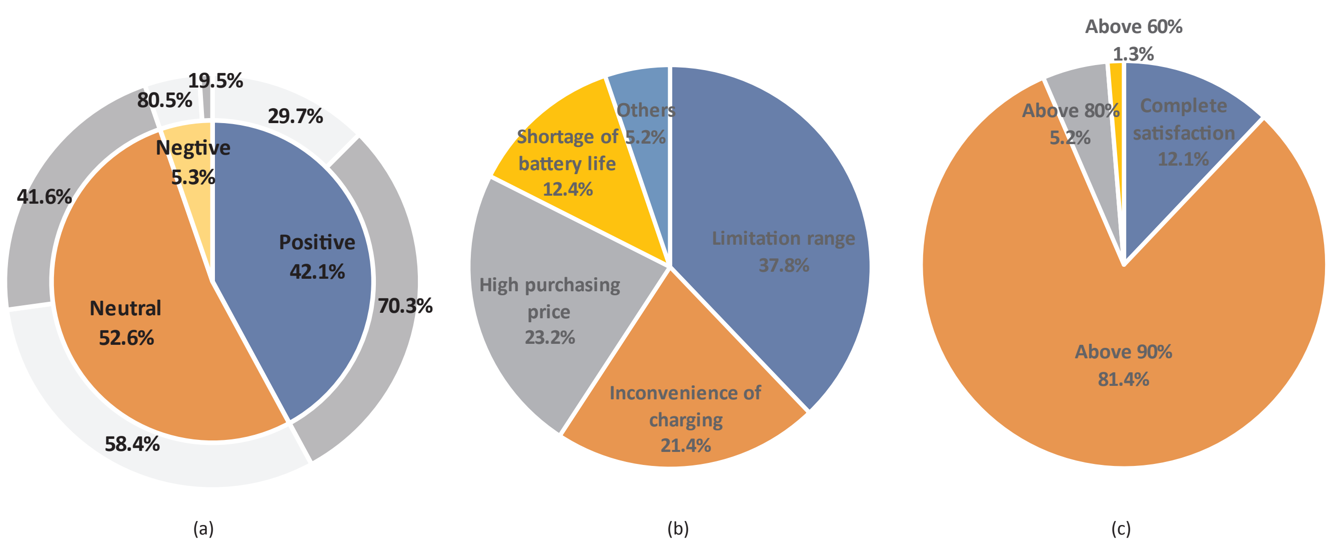

Fig. 1. Results of surveys of the purchase intent and factors of concern for BEVs. (a) Survey results of the purchase attitudes for BEVs. (b) Survey results of the factors of concern for BEVs. (c) Survey results of expectation of satisfying the driving travel demand for adopting BEVs.

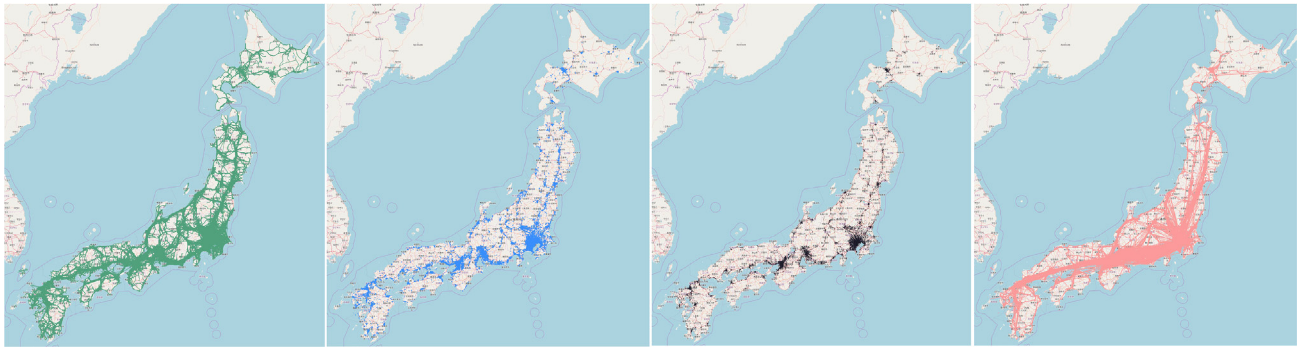

Fig. 2. Results of human-travel-mode recognition and classification. (a) Vehicle travel track. (b) Bicycle travel track. (c) Walk travel track. (d) Train travel track.

E battery-specific energy target [31] as the battery capacity standard. The Nissan Leaf (new) is a new BEV expected to hit the market at the end of 2017 [32]. In Fig. 3, E_O is the daily travel energy demand in all periods, E_H is the holiday daily travel energy demand, SR is satisfaction rate of the daily driving travel demand, and AVER is the weighted average of the DAP. The AVERs of the key standards of the battery capacity are enclosed in parentheses in red.

The results show that in different scenarios, the DAP results vary widely. Taking the Nissan Leaf as an example, the average DAPs were 90.3%, 84.2%, and 76.3% in the three scenarios. For an SR in the range of 90–100%, the maximum difference in the DAP reached 14.0%. A difference of 6.1% between the holiday and overall period was also observed. The results demonstrate that the impacts of the demand satisfaction requirements and the selection of the study period on the analysis of the adoption potential are significant. Even for the same scenario, the difference in the DAP was wide between different groups of people. In scenario 3, for example, the Toyota Scion iQ, which is targeted at city travel, could meet 62.5% of vehicle travel demands of the LVTs, and the latest Nissan Leaf (new) could meet about 85.2% of the demands. However, the SRs of these two cars were only 39.8% and 69.6% for OHVTs. This is also one of the reasons for why the LVTs occupy a large proportion of people holding a positive attitude towards BEVs. Considering the DCAs, the diversification of BEV products is an important factor influencing the adoption potential.

6.4. Charging interval analysis

On the basis of the above findings, the existing BEVs could meet most of the daily vehicle travel demand, which is consistent with previous studies. However, this result disagrees with that of the previous survey (Fig. 1), where 37.9% of people think the limitation range of a BEV is the main concern. This shows that a multiday charging interval (charging inconvenience) is taken into account when people make a purchase decision. Therefore, the DAP is a relatively promising metric for analyses of the adoption potential of BEVs. Thus, we introduced a new dimension to represent the charging convenience: the CI. When the charging infrastructure system is more comprehensive and the charging speed is faster, the CI will be smaller. Therefore, the degree of charging convenience can be characterized by the CI to a certain extent. Furthermore, the WAP was defined (Section 5.3). On the basis of the detailed proportion of the survey results (Fig. 1c), a proportional weight is multiplied with the percentage of vehicles that could be covered on one charge. The WAP represents the diversity of the expected demand satisfaction. On the basis of the GPS data, the WAP was calculated using the CIs of different types of travelers (Fig. 4). The results show that if the construction of charging infrastructure is not sufficiently mature, the adoption potential is not as promising as concluded in previous studies, and the difference may be unexpectedly significant. Taking the Nissan Leaf as an example, with a CI of 4, the average WAP was only 71.0%, and with CI = 7, the average WAP dropped to 57.4%. From these analyses, we found that given the current levels of BEV and battery technologies, the sensitivity of the charging convenience to the adoption potential of BEVs is much greater than that of battery capacity. Although 37.9% people in the previous survey considered the limitation range as the main concern for adopting BEVs, the underlying reason could be that many of these people have difficulty finding convenient charging facilities and resources, while the currently available BEVs cannot meet their multiday driving demand without charging. Therefore, compared to increasing the battery capacity, improving the public charging infrastructure and developing fast-charging technology are much more efficient at increasing the adoption potential of BEVs.

6.5. BEV policy target response

The Japanese Ministry of Economy, Trade and Industry has proposed the next-generation vehicle development strategy. This strategy is targeted at spreading the market share of BEVs to 20–30% [30]. Achieving this target requires the government to propose more active preferential policies and depends on technological progress and the construction of charging facilities. Therefore, this is a complex sociotechnical problem with multiaspect coupling. Here, three demand models were introduced to characterize people's concerns about P&M costs: a high-cost model, reference model, and low-cost model. Depending on the level of technology and the government subsidies in the future, the P&M costs of a BEV may be high, balanced, or low. These models assume that 35%, 40%, and 45% of people will adopt BEVs and that their various vehicle travel demands are met. For each model, a detailed technical index, the BEV battery capacity, and the corresponding CI were developed to achieve the policy target (Fig. 5). In Fig. 5, the red, blue, and green grid areas represent the high-cost, reference, and low-cost models, respectively. The upper line of each area represents the corresponding battery capacity and CI for the 30% market share target, and the lower line is for the 20% market share target. We used the Nissan Leaf as the benchmark. In the high-cost model, the target of 20% market share could be easily achieved with the CI in less than 7 days. However, for a target of 30%, more construction of charging infrastructure is required to decrease the CI to 2.62 days. In the reference model, a CI of 5.24 days was required for the same target. In contrast, in the low-cost model, a target of 30% could be easily achieved given the 40-kWh battery capacity. If the ARPA-E battery-specific energy target is reached, it will decrease the pressure on the government, but there still is a large gap in the CI demand in the high-cost model. These results show that the impact of the degree of market recognition on the adoption potential of BEVs is also more sensitive than that of the battery capacity. Increasing purchasing subsidies and boosting the advancement of electrification technologies for increasing the battery life and reducing the production cost are highly effective

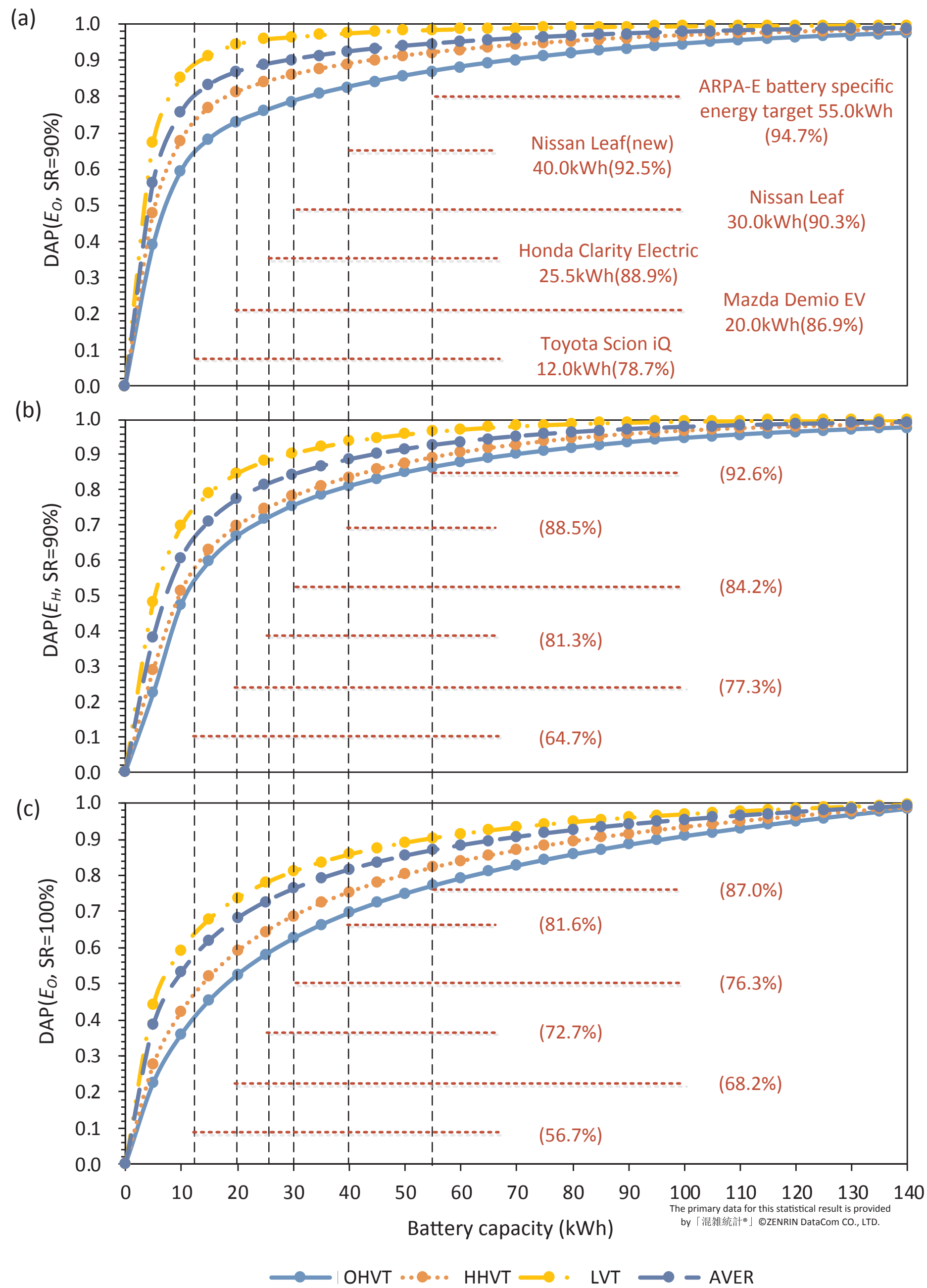

Fig. 3. Results of a DAP analysis for different scenarios: (a) meeting 90% of the daily travel energy demand in all periods, (b) meeting 90% of the holiday daily travel energy demand, and (c) meeting 100% of the daily travel energy demand in all periods.

responses to the policy target. However, most existing BEVs have a battery capacity that is less than 40.0 kWh; that is, this benchmark may actually decline. In the scenarios of the high-cost and reference models, the government may face greater pressure to promote the construction of charging infrastructure.

6.6. Discussion

Our study shows that DCAs such as the differences in travel habits and the performance expectation have significant impacts on the adoption potential of BEVs. Given the current level of BEV battery technology, many technical and policy improvements are much more effective than advances in the battery capacity to increase the adoption potential of BEVs. At the industrial level, it is necessary to promote electrification technologies for fast charging, increasing the battery life, and reducing the production cost. At the governmental level, improving the public charging infrastructure and increasing purchasing subsidies would significantly enhance the market potential of BEVs.

We found that LVTs are more active in adopting BEVs than HVTs. Therefore, research on travel behaviors and market surveys of such people will be significant. When considering the differences in travel habits, the diversification of BEV products is an important factor influencing the adoption potential.

We also found from the survey results that people's concern for the limitation range is contrary to the results of the DAP analysis. This illustrates that the current infrastructure of charging systems does not meet the personal daily charging requirements. The convenience of charging is another key factor. We introduced the CI metric to reflect the convenience of charging. Our results show that when the CI is 4 days, the currently available BEV technology can satisfy 71.0% of the

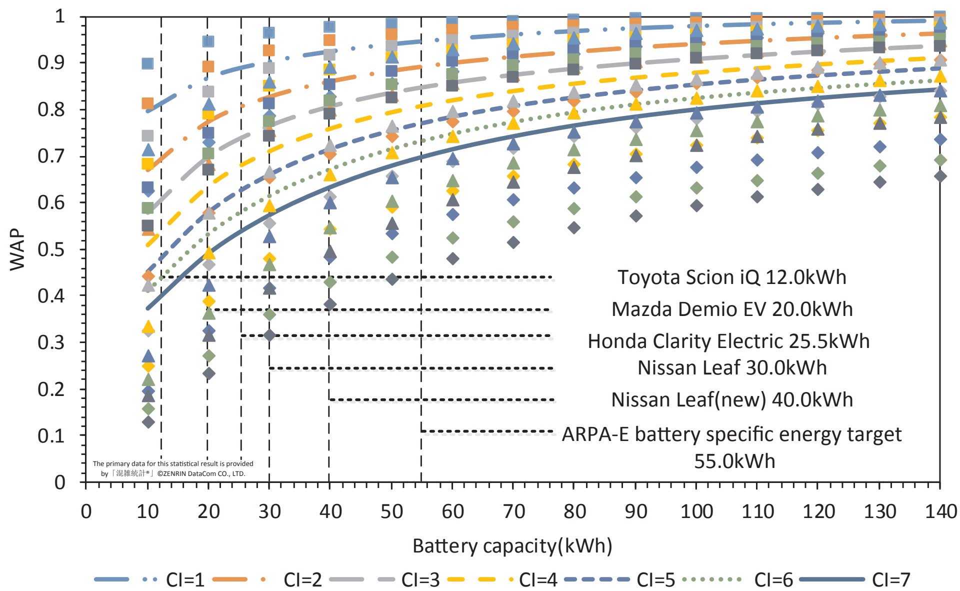

Fig. 4. Weighted vehicle adoption potential for different charging intervals. ■ Represents LVTs, ▲ Represents HHVTs, ◆ Represents OHVTs and the colored lines represent the weighted averages of the WAP.

vehicle travel demand, and when the CI is 7 days, this value drops to 57.4%. With the current construction conditions for public charging systems and charging technologies, the adoption potential of BEVs may not be as promising as the conclusions of previous studies. The overall results show that there still exists a large pressure on the government to respond to the target.

Meanwhile, with rapid development of the global market of BEVs, the domestic product performance and market demand of other large economies such as USA, Europe and China are not much different with Japan [5]. On the basis of this, the qualitative conclusions of this paper will be also serviceable for guiding the other governments to formulate carbon emission reduction policies.

7. Conclusion

In this study, the adoption potential of BEVs is estimated on the basis of DCAs. This paper presents detailed sociotechnical indexes for achieving the policy target and developing strategies for the next generation of vehicles. Moreover, BEV companies could use the results of this study to optimize the diversification of BEV products for DCAs to improve the overall market demand. This paper also proposed a universal methodology frame for the adoption potential analysis of BEVs based on the smart phone GPS data. By using this frame, the detailed prediction for electrification developments of vehicles in other parts of the world could be predicted.

However, the data acquired in this study were affected by several factors such as the loss of signal or battery power, and it is difficult to distinguish the travel tracks of public and private vehicles on the basis of mobile-phone GPS data. This may cause analytical errors in the final results. Nevertheless, a larger number of samples of the population and a larger duration were taken to reduce the degree of impact of these special conditions as much as possible. In addition, many further studies are still required for a more comprehensive conclusion. For example, the relation between the maturity level of the charging system and the CI and the exact impacts of a policy and price variation on people's attitude towards purchasing BEVs need to be investigated in further detail. In addition, the electrification development of other functional vehicles (such as lightweight commercial vehicles, heavy

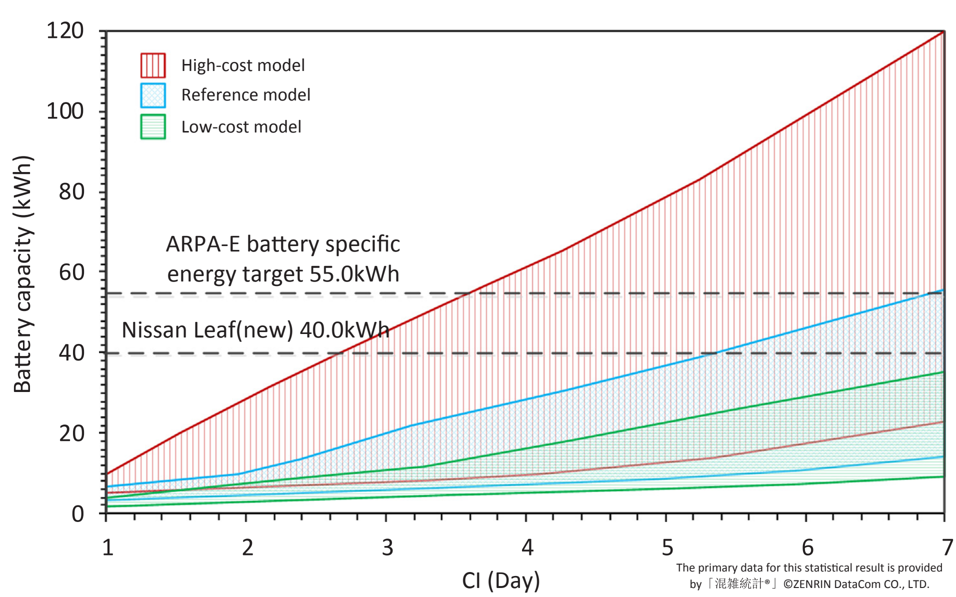

Fig. 5. BEV policy target response.

truck and road tractors for freight delivery) should be further studied. Meanwhile. the detailed load pattern identification for the optimization of the electric network operation is also needed to be considered into the vehicles electrification analysis [33]. Such further studies will play important roles in the technological development, market development, policy-making, and quantitative analysis of a reduction in emissions considering BEVs.

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